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REVIEW ARTICLE FEEDING THE FUTURE

Precision farming: A review of artificial intelligence applications in broiler poultry farming*

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Abstract

The global poultry industry is a critical sector, tasked with meeting the increasing demand for animal protein. Despite its growth and efficiency, it faces challenges, including enhancing productivity, optimizing resource utilization, and ensuring animal welfare. Addressing these challenges requires innovative solutions to improve both the efficiency and sustainability of poultry production. This paper presents an in-depth analysis of how advancements in artificial intelligence (AI) and machine learning (ML) technologies are being integrated into poultry farming to revolutionize its practices. We explore the application of AI in monitoring systems, smart poultry houses, and automated management practices that significantly enhance production metrics and animal welfare. Our study delves into various AI-driven methods, such as predictive modelling, real-time environmental monitoring, and precision feeding systems. Furthermore, the research identifies the current limitations and future potential of these technologies in facilitating a shift towards more responsive and responsible poultry farming practices. Our findings suggest that embracing AI technologies not only contributes to the economic viability of poultry farms but also aligns with ethical standards and sustainability goals, indicating a promising direction for the future of poultry farming.

Keywords

Animal welfare, environmental factors: machine learning, poultry monitoring

Introduction

The poultry industry plays a vital role in meeting the global demand for animal protein, with poultry meat and eggs being significant sources of nutrition for billions of people worldwide (Windhorst 2006). Enhancing productivity involves advanced management practices and disease prevention measures to maximize output and minimize input. Optimizing resource utilization entails precision nutrition, efficient water management, and the adoption of practices to reduce costs. Additionally, the economic feasibility of AI technologies, such as IoT-enabled systems has been shown to reduce operational costs by up to 20% through optimized resource use and labor efficiency (Szőllősi et al.,2021). Ensuring animal welfare requires providing appropriate housing conditions, disease control measures, and humane handling practices throughout the production cycle. AI technologies also align with ethical standards by reducing animal stress through non-invasive monitoring, supporting humane production practices

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(Neethirajan et al. 2024). Addressing these challenges demands a comprehensive approach integrating technological innovation, effective management strategies, and industry-wide cooperation to sustainably and ethically meet the demands of poultry production.

The proportion of global meat output attributed to poultry has consistently risen (Scanes et al. 2007), even as beef's contribution has decreased (Nierenberg 2021). Among livestock sectors, poultry farming stands out for its superior efficiency in transforming feed grains and protein sources into edible meat. However, pork accounted for the largest share of world meat production up until 2020 when it was surpassed by poultry as illustrated in Fig. 1.

In 2021, a total of 70,663,503,000 chickens were produced and processed globally. Africa, with an estimate population of 1.4 billion people, only produced 8% of the global production, with a chicken-produced-per-person ratio of 3.79 in 2021, while Asia and Europe had a ratio of 7 and 15.1, respectively, in the same period (Pison 2019; Léridon 2020). Almost half of the production comes from Asia, with a head count of almost 33 billion chickens produced in 2021. Fig. 2 displays global poultry meat production versus global pork meat production over the past 30 years, while Fig. 3 illustrates the produced chickens per continent for 2021.

In response to production challenges, advancements in AI technology have emerged as promising solutions, particularly in the realm of smart poultry houses and monitoring systems (Kumar et al. 2025). ML and AI have become integral components of modern technological advancements, with their applications spanning various industries, including agriculture. In the poultry sector, leveraging ML and AI technologies offers promising opportunities to enhance productivity, optimize resource management, and improve animal welfare. However, discerning the differences between ML and AI is crucial for elucidating their specific roles and functionalities within poultry farming operations.

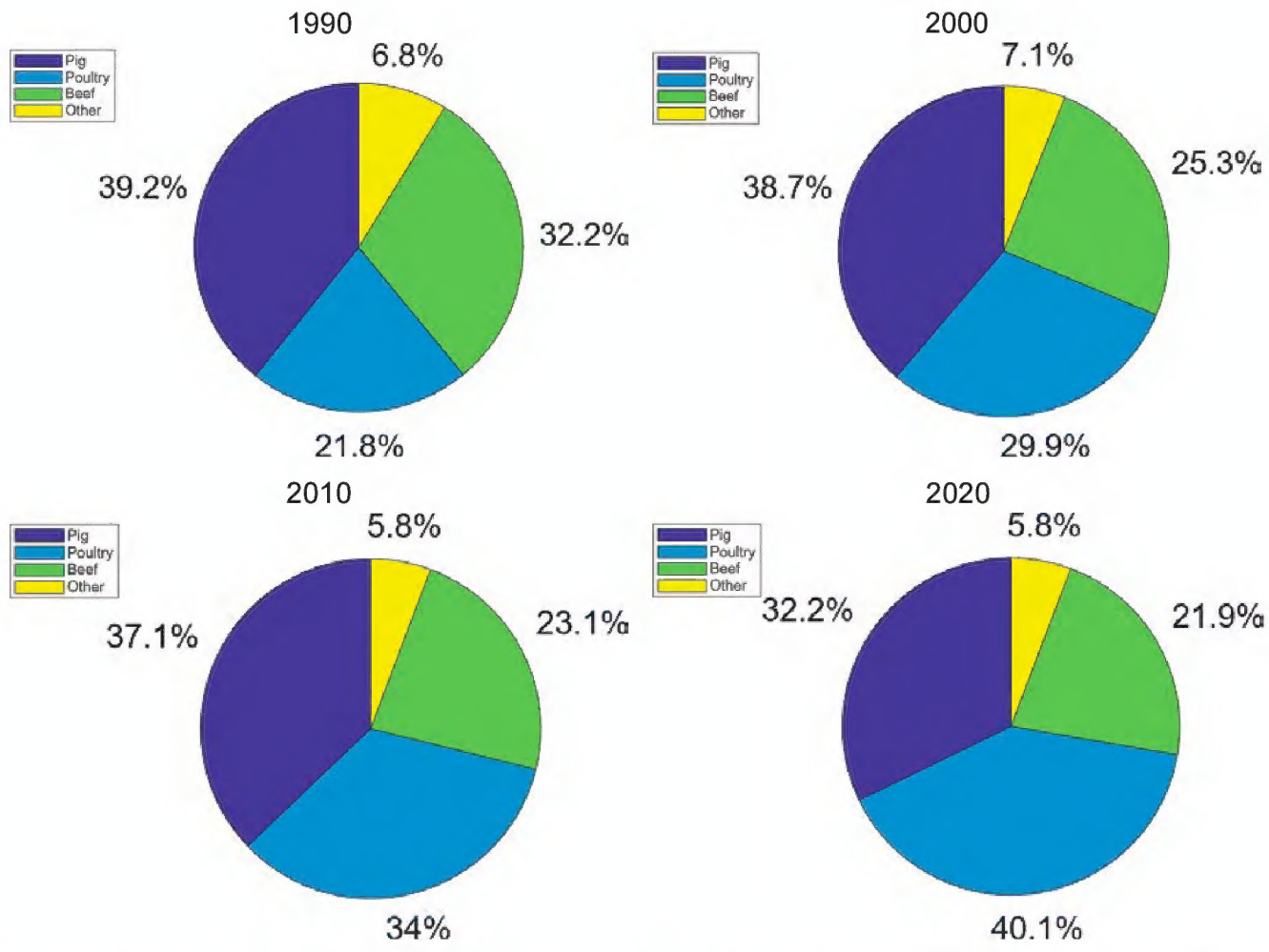

Figure 1. Global meat production of the last 30 years. Pie charts generated by the author using data from Delgado et al. (2020).

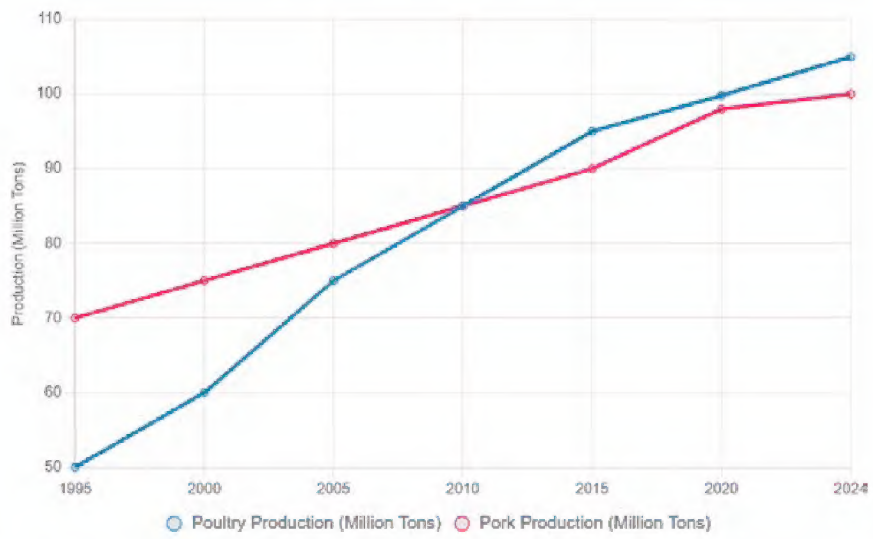

Figure 2. Poultry vs pork meat production. Graph generated by the author using data from Food and Agriculture Organization of the United Nations (2024),

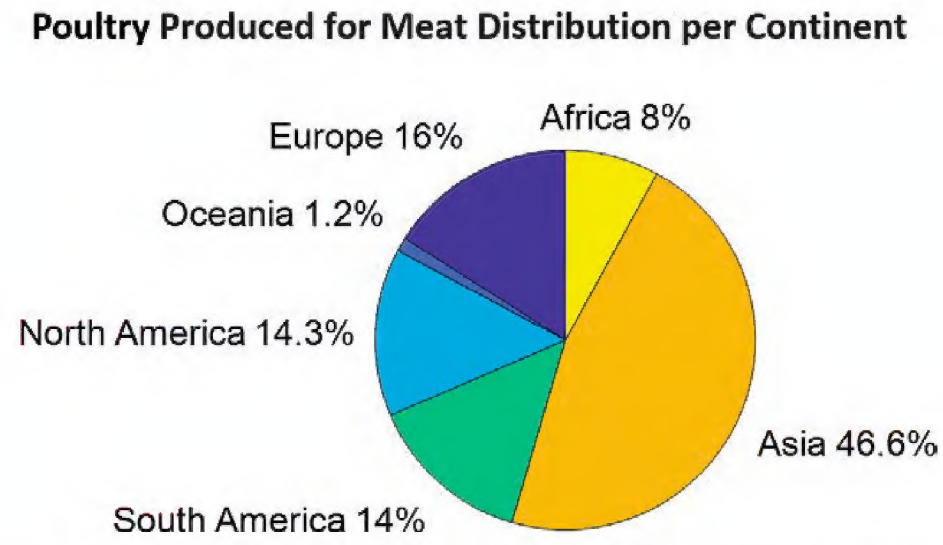

Figure 3. Meat chickens produced per continent. Pie chart generated by the author using data from Delgado et al. (2020).

Methods

This review synthesizes research exploring the role of machine learning (ML) and artificial intelligence (AI) in advancing the commercial broiler sector. A systematic desktop analysis was performed, targeting global studies on ML and AI tools for poultry health tracking and welfare enhancement. The scope encompassed publications from the last decade, including journal articles, review papers, book sections, dissertations, brief research notes, and industry reports. Each source was evaluated against the main goals of the study, with findings informing targeted suggestions for future investigations to strengthen monitoring systems and promote broiler well-being.

Results and discussion

Measuring critical factors that influence poultry in a commercial broiler house throughout their life cycle can help identify certain deficiencies in poultry growth rate and wellness (Mana et al. 2024). The figure below illustrates the factors that are measured that directly influence poultry growth, wellness, and health. In this research, we focus on measuring food and water intake, all the environmental factors inside the broiler house, as well as services that impact poultry wellness, and finally how AI technologies (Taleb et al. 2024; Ajobola et al. 2025) are used in commercial broiler houses (Fig. 4).

Poultry food and water intake monitoring

Automation plays a crucial role in smart poultry houses, particularly in feeding and watering systems. Automated feeders and drinkers are strategically placed throughout the facility, utilizing AI algorithms to optimize feed distribution and water consumption. These systems adjust feeding schedules and portion sizes based on factors such as bird age, weight, and production goals, maximizing feed efficiency while minimizing waste. Additionally, AI algorithms analyze consumption patterns to detect any anomalies or health issues, enabling timely intervention. In broiler poultry farming, applying AI to feeding and watering systems involves the integration of various sensors and hardware components to automate and optimize these processes. Feeding systems include feed level sensors, feed dispensers, weight sensors on the feed dispensers, augers, and conveyors. Watering systems include water level sensors, flow sensors, pressure sensors, valves, pumps and communication interfaces to enable communication between sensors, actuators, and AI control systems. By integrating these sensors and hardware components with AI algorithms and control systems, broiler poultry farmers can automate and optimize watering and feeding processes to improve efficiency, productivity, and bird welfare in poultry farming operations.

Food intake

A novel technique (Aydin et al. 2014) employs acoustic analysis to automate feed consumption tracking in broilers. Researchers created a detection model to identify distinct pecking noises from individual birds and correlated these auditory signals with actual feed amounts. Validation involved comparing algorithm outputs to standard measurements from electronic scales and video recordings (Yo et al. 1997; Gates et al. 2008). Over three days, audio data was collected from 12 male broilers (28 days old) using a microphone mounted near the feeder. Each bird participated in three controlled trials—yielding 36 sessions—during which a precision weighing unit logged feed removal automatically. Intake was computed by adjusting for spillage. The model achieved 93% accuracy in pecking detection with a 7% false positive rate and revealed a strong link between pecking frequency and feed volume (Aydin et al. 2014). This audio-based method supports continuous, non-intrusive monitoring across the flock's growth cycle, advancing precision livestock management. Implementing it in large-scale housing, however, demands strategic microphone placement and noise isolation.

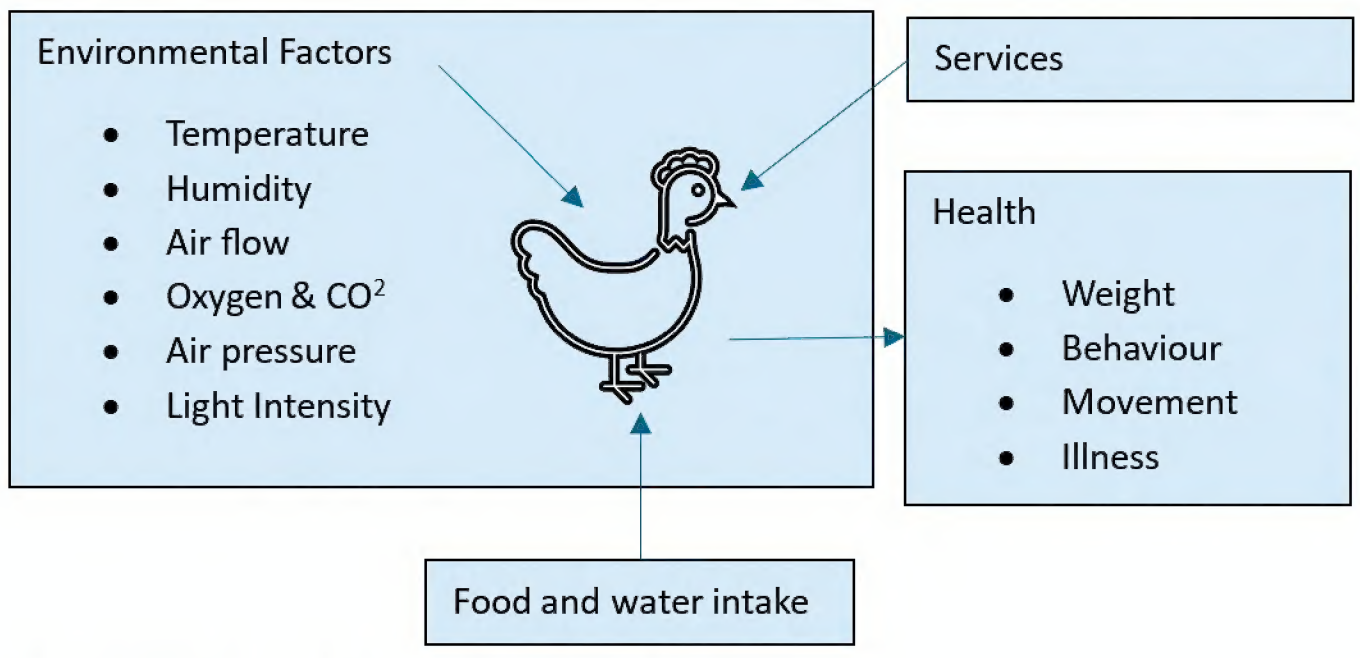

Figure 4. Critical factors to measure inside the broiler house

Building on this foundation (Aydin et al. 2015), a refined system was developed for group-level feed monitoring using live audio processing. Pecking sounds from 10 male broilers (39 days old) were captured via a feeder-mounted microphone, while overhead cameras recorded feeding activity. A reference weighing platform (Puma et al. 2001) simultaneously tracked feed disappearance. The updated algorithm processed concurrent pecking events from multiple birds and estimated group intake. Results showed a robust correlation (R^2 = 0.994) between sound-derived and scale-measured values, with 86% of intake accurately quantified. These studies (Puma et al. 2001; Gates et al. 2008; Aydin et al. 2014, 2015, 2018) demonstrate scalable, real-time group monitoring. Reported feed waste reductions of up to 15% (Jebari et al. 2023) could yield 10–15% cost savings in AI-integrated broiler facilities (Campbell et al. 2025).

Another system (Peng et al. 2022) enables precise individual tracking of feed intake and body mass in poultry through an integrated automated platform. Key components include a controlled feeding gate, RFID identification, high-resolution scales for body weight and feed, and a drop-capture mechanism for spilled feed. Signal conditioning via analogue circuits and digital filters improves measurement reliability. A sliding partition isolates birds for single-access feeding, ideal for young stock. Trials revealed daily weight gains of ~8.88 g and a feed conversion ratio (FCR) of ~4.4. The setup effectively captures growth and consumption patterns in controlled settings. While effective for research with young birds, scaling this isolation-based design to commercial barns housing 30,000–50,000 broilers remain logistically complex and infrastructure-intensive.

Water intake

When the water intake of poultry is not correct, several issues can arise, impacting their health, welfare, and overall production performance. Some of the key issues include dehydration, heat stress, nutrient absorption, health issues, behavioral problems, and reduced production performance. Overall, ensuring correct water intake is crucial for maintaining the health, welfare, and productivity of poultry. Water intake patterns, as observed through collected data, offer valuable insights that can aid in diagnosing various issues related to feed quality and flock health in broiler chickens. Monitoring water intake levels provides an indirect indicator of the birds' overall well-being and can serve as an early warning system for potential health or management issues.

Water meters (Mohammed et al. 2019; Yao et al. 2021) serve as vital management tools for monitoring daily water usage in poultry houses. However, conventional mechanical water meters pose limitations in accurately measuring water flow rates for young birds, particularly those less than four days old. The advent of ultrasonic water meters has revolutionized this aspect by enabling precise measurement of water usage within minutes of chicks being introduced into the house (Yao et al. 2021). When coupled with modern house controllers and data logger systems, ultrasonic meters facilitate real-time data collection, storage, and visualization of water consumption patterns, thereby allowing early detection of management issues during chick rearing.

A series of field trials (Yoa et al. 2021), was conducted across multiple farms, employing ultrasonic water meters connected to house controllers and data loggers. Through these trials, various common management-related issues affecting broiler farms were documented based on water usage data. For instance, one trial revealed a drinker leakage issue detected within 24 hours of chick placement, leading to a significant increase in water usage and uneven distribution of water on the house floor. Additionally, anomalies such as continuous water usage during dark periods due to malfunctioning house lights were identified, impacting bird welfare and growth.

Furthermore, insights garnered from water usage data highlighted correlations between bird density at placement and water usage, with implications for flock uniformity and performance. Disparities in bird weights between different areas of the house were attributed to variations in bird density, resulting in reduced grower pay. The utilization of ultrasonic water meters facilitates continuous monitoring from chick placement to grow-out completion, offering valuable insights for optimizing chicken management practices.

Despite being a relatively low-cost investment, the ultrasonic water meter yields significant returns by enhancing poultry management efficiency and performance. Its ability to provide real-time monitoring and early detection of management issues underscores its value in optimizing chicken management practices and maximizing returns on investment. Maintaining correct water intake is crucial for ensuring the health, welfare, and productivity of poultry, with deviations from optimal levels potentially leading to various issues such as dehydration, heat stress, and reduced production performance. The utilization of ultrasonic water meters, coupled with modern house controllers and data logger systems, offers a transformative solution for monitoring water usage in poultry houses.

Environmental factors

Poultry species are very susceptible to temperature and humidity fluctuations because they do not sweat and cannot regulate their body temperature. They lift their wings to allow airflow to cool off. The environmental conditions (Zhang et al. 2024) within poultry houses play a crucial role in determining the health and performance of birds. Among these variables, litter moisture stands out due to its significant impact on various aspects of poultry management. It affects house ventilation systems, contributes to ammonia production, and influences bird health, making it a key factor to monitor and manage effectively.

Environmental conditions deviating from the accepted norms may result in reduced feed intake (and thus slower growth) (Corkery et al. 2013a), high-stress levels (Abu-Dieyeh 2006), and high mortality rates (Ferreira et al. 2011). To maintain ideal welfare status, continual access to water is required (European Commission Report 2000).

Temperature

Temperature regulation is paramount in smart poultry houses, as it significantly impacts the overall success of the growth process (Akşit et al. 2006; El-Rahman et al. 2017). Poultry buildings must maintain optimal conditions, including internal temperature, humidity, air pressure, and air quality, to ensure the well-being and productivity of broilers. Proper temperature control is particularly crucial to mitigate thermal stress among birds, which can result in reduced weight gains, compromised health, and increased mortality rates. Throughout the life cycle, indoor temperatures in broiler farms must be adjusted according to the birds' developmental stages. Initially, temperatures should be maintained at around 33 °C to accommodate the birds' inability to regulate their heat balance. As birds mature, temperatures should gradually decrease, reaching a minimum of 21 °C by the sixth week of life to facilitate proper thermal conditions. Overheating during the second stage of rearing can adversely affect broilers' appetite and growth rates, emphasizing the importance of maintaining temperatures between 13 °C and 21 °C. Ensuring birds remain in optimal thermal conditions for a minimum of 8 hours per day is essential for their overall well-being and successful growth. There are many severe consequences of exceeding the proper temperature level in broilers, such as lower growth, higher death rate, poorer quality of droppings, increased sickness, and increased consumption of vitamins (Akşit et al. 2006).

Humidity

A study (Kasakula et al. 2021) introduces an energy-optimized control algorithm that leverages the interdependence of temperature and humidity to manage environmental actuators in broiler housing. By performing real-time psychrometric computations at the edge, the system forecasts post-actuation conditions and selects the most efficient actuation sequence. Benchmarking against conventional control logic revealed reduced power consumption and elimination of rapid on–off cycling. These improvements support more sustainable climate management in automated poultry facilities.

Another investigation (Lorencena et al. 2020) outlines a comprehensive platform for regulating and supervising temperature and humidity in poultry environments. The architecture integrates sensor arrays, advanced control algorithms, and cloud connectivity to enable precise environmental oversight. The authors detail the modelling, design, and deployment of a supervisory controller that ensures safe, non-blocking actuator behaviour while adhering to operational constraints. The implemented solution features a dual-interface web portal for remote visualization of system states and optional manual intervention, enhancing operational flexibility and responsiveness in modern poultry production.

Air quality

Key environmental factors influencing broiler performance and energy efficiency in production facilities include air temperature, relative humidity, lighting, airflow velocity, and air quality—especially CO_2 and NH_3 levels (Corkery et al. 2013b). Despite its importance, air quality is frequently deprioritized by producers focused on minimizing heating and feed expenses. Notably, CO_2 concentrations exceeding 3000 ppm (Corkery et al. 2013b) showed no significant impact on growth rates. However, a robust correlation emerged between relative humidity and NH_3 accumulation, validating the common practice of using humidity readings as a proxy for ammonia build-up. A detailed examination of air quality's implications for poultry health and welfare will be presented in a subsequent section.

Light

In modern intensive broiler operations, lighting parameters—including wavelength, intensity, and scheduling—significantly influence bird behaviour, growth, and welfare (Kristensen et al. 2007; Deep et al. 2010). Light-emitting diodes (LEDs) have become the preferred choice in poultry housing, delivering either single-color or broad-spectrum illumination that closely mimics sunlight, surpassing the capabilities of traditional fluorescent bulbs. Key benefits of LEDs encompass extended operational durability, diminished power usage, and lower upkeep expenses (Huber-Eicher et al. 2013; Soliman et al. 2020). Research has demonstrated that monochromatic light positively influences various production parameters (Cao et al. 2008; Mendes et al. 2013; Zhang et al. 2014). It is important to note that artificial lighting can impact poultry differently than humans due to birds having four types of cones in their retinas, as opposed to humans' three types (Lewis et al. 2000). Poultry can perceive light in the range of 315 to 750 nm, with many behavioral responses being stimulated by visual cues (Soliman et al. 2020). Poultry are capable of detecting UV-A light within this range (Riber 2015).

Studies (James et al. 2020) suggest that exposure to UV-A wavelengths (100–400 nm) can reduce mortality rates (by 75% compared to control groups) and have positive economic implications for broiler production, despite potentially affecting weight gain negatively during the production period. UV light exposure can aid in the synthesis of vitamin D in poultry, which is essential

for calcium absorption and bone health. This 75% reduction in mortality rates through UV-A light exposure (James et al. 2020) not only enhances productivity but also aligns with ethical welfare standards by minimizing suffering (Neethirajan et al. 2024). Adequate levels of vitamin D can help prevent skeletal disorders such as rickets and improve overall bone strength in broiler poultry. Moreover, UV light has antimicrobial properties, which can help reduce the microbial load in poultry houses. By controlling bacterial and fungal growth, UV light contributes to maintaining a cleaner and healthier environment for broiler chickens, thereby reducing the risk of disease transmission and improving flock health.

Poultry exhibit increased sensitivity to red light (630–780 nm), which has been reported to provoke aggressive behavior (Prayitno et al. 1997; Zhang et al. 2014). Near-infrared light ranges from approximately 700 nm to 1,400 nm, and therefore, heat lamps or cameras using infrared can have an impact on poultry behavior. Illumination at a colour temperature of 6065 K, enriched with blue wavelengths, has been linked to enhanced final body weight (BW) and greater breast meat production in broilers (Riber 2015). Additionally, integrating blue and green spectra throughout the rearing period can positively modulate immune function (Arowolo et al. 2019; Lucena et al. 2020).

Weight

Automatic weighing systems, such as pan scales, offer a solution that significantly reduces the need for manual labor in poultry weight monitoring. Pan scales, suspended low above the litter, are equipped with electronic calculating units to measure the weight of individual birds upon stepping onto the platform (Chedad et al. 2000). Placing these scales strategically, such as near drinkers/feeders or as additional enrichment, facilitates the collection of a higher volume of measurements. In the case of laying hens, scales positioned within nests (Larios et al. 2013), notably at the entrance, have been employed, drawing inspiration from monitoring techniques utilized in wild bird studies. Importantly, automatic measurements mitigate the stress associated with traditional methods involving human handling and interactions (Wang et al. 2018). Furthermore, real-time access to collected data empowers farmers with timely insights for informed decision-making (Fig. 5).

Utilizing 3D depth images from the Kinect sensor, this study (Mortensen et al. 2016) explores the potential of camera-based weighing systems for assessing broiler weights in a commercial production setting. The developed system employs a cost-effective 3D camera (Kinect) capable of capturing depth images, thus mitigating issues related to changing light conditions within the broiler house through its integrated infrared light source. An innovative image processing algorithm is introduced, utilizing a range-based watershed algorithm for image segmentation, followed by the extraction of twelve distinct weight descriptors. Subsequently, individual broiler weights are predicted using a Bayesian artificial neural network, with four alternative weight prediction models also assessed. Testing conducted in a commercial broiler house with 48,000 broilers (Ross 308) over the final 20 days of the rearing period yielded promising results. Comparison against reference weights obtained via a traditional platform scale demonstrated an average relative mean error of 7.8% on a separate test set comprising 83 broilers and approximately 13,000 manually annotated images. Notably, errors tended to increase toward the end of the rearing period due to higher broiler density, with absolute errors ranging from 20–100 g in the first half of the period and 50–250 g in the latter half. The system exhibits potential for broader application in commercial broiler pens, including activity analysis and health monitoring functionalities, thus paving the way for enhanced management practices and improved productivity in poultry production (Amraei et al. 2017; Nyalala et al. 2021).

Figure 5. Platform scale and communication terminal installed in poultry house.

Traditional methods of weighing broiler chickens, such as steelyard or platform scales, are known for their time-consuming and labor-intensive nature, often resulting in stress-related behavior among the birds during the weighing process. Moreover, existing 3D camera-based weighing systems encounter limitations, including the

inability to weigh broiler chickens beyond the monitoring area and poor weight prediction, particularly when birds are in motion, such as flapping their wings (Nyalala et al. 2021). To address these challenges, a novel, simple, and cost-effective weighing system with enhanced stability and accuracy has been developed (Li et al. 2023). This system incorporates a validity value extraction method derived from dynamic weighing, alongside an improved amplitude-limiting filtering algorithm and a BP neural network model. The BP neural network model utilizes parameters such as daily weight gain, day-age, average velocity, and weight data post-filtering algorithm as input layers, thereby enhancing the system's

Activity monitoring

Regular observation of broiler flocks yields critical data on welfare conditions, ensures compliance with baseline standards, and enables timely interventions (Campbell et al. 2023; van der Eijk et al. 2022). Computer vision systems hold strong promise for continuous, automated welfare evaluation, offering an objective and bio secure alternative to labour-intensive manual assessments. Despite progress, existing vision-based solutions fall short of supporting full automation in commercial-scale operations. To address this gap, the study (Campbell et al. 2023) evaluated the feasibility of scalable, computationally efficient computer vision pipelines for detecting individual broilers and tracking their interaction with resources in both controlled and farm environments. The approach combined instance segmentation via Mask R-CNN with zone-specific classification to assign detected birds to functional areas. Three models were trained using distinct annotation sets: Model A (research facility data), Model B (commercial farm data), and Model A+B (combined dataset). Detection performance was robust across settings, achieving F1 scores above 0.99 (Model A, research) and 0.83 (Model A+B, commercial) at an IoU threshold of 0.75. Resource-use monitoring using Model A+B delivered high accuracy for feeders, enrichment bales, and perches (F1 > 0.93), though drinker tracking underperformed (F1 = 0.28), likely due to evaluation limitations. These results (Campbell et al. 2023) mark an important advance toward non-invasive, automated welfare monitoring in large flocks. By aggregating per-frame location data, the system enables precise quantification of resource engagement, laying the foundation for vision-driven welfare assessment in commercial poultry production.

Camera-based systems offer a promising avenue for automating broiler behaviour surveillance, reducing reliance on time-consuming manual inspections. This research (Baxter et al. 2020; Campbell et al. 2024) develops a prototype vision platform for detecting and following individual birds, facilitating the identification of activity patterns via unsupervised clustering of 2D movement paths. A convolutional neural network detector, fine-tuned on annotated images, delivered strong performance metrics: precision of 0.98, recall of 0.90, and F-score of 0.94. Using a detection-followed-by-tracking paradigm, the framework maintained reliable multi-bird trajectories across sequences, attaining a multi-object tracking accuracy of 74.7%. Fig. 6 illustrates identifiers for individual chickens on the platform scale (Fig. 6a) and in the broiler house (Fig. 6b).

Subsequent application of a component-based feature saliency Gaussian mixture model (CFSGMM) facilitated the objective clustering of trajectories based on spatio-temporal information, revealing three distinct activity classes (Dawkins et al. 2009). Validation of the proposed method on one-minute monocular video sequences within a commercial rearing environment yielded promising results (Campbell et al. 2024), with trajectory clustering achieving substantial agreement (ranging from 6.0% to 99.7%) when compared to human observation. This computer vision system (Hong et al. 2019; Lomanov et al. 2019; Li et al. 2021) exhibits potential for real-time monitoring of short-term changes in broiler activity associated with on-farm events and holds promise for monitoring longer-term welfare states. Further development of detection and tracking systems is anticipated to enhance the performance of trajectory clustering, paving the way for broader applications in broiler management and welfare monitoring (P´erez-Escudero et al. 2014; Yuan et al. 2017; Wurtz et al. 2019).

Figure 6. Camera tracker assigns individual IDs to each chicken. **a.** on the platform scale; **b.** in the broiler house.

In an investigation, the authors (Yang et al. 2021) utilized signal processing techniques to determine the sound frequency ranges of various sources, including bird vocalization, fan, feed system, heater, wing flapping, and dustbathing, in a commercial Ross 708 broiler house across different bird ages. Additionally, they examined the behavioral frequencies of wing flapping and dustbathing (Yang et al. 2021). Results indicated that vocalization frequencies in broilers declined with advancing age, whereas fan noise typically shifted upward over the production cycle. The higher-end spectra for feed delivery, heating units, wing flapping, and dustbathing activities surpassed 18,000 Hz. Additionally, strong inverse relationships emerged between bird age and the occurrence rates of wing flapping and dustbathing behaviours (Dörfler et al. 2017; Sheng et al. 2020; Kate et al. 2025). In summary, these observations provide essential data for evaluating broiler health, welfare, and activity patterns via audio signal analysis (Venkatraman et al. 2025); however, additional studies are required to extend applicability across diverse housing setups and genetic lines.

Illnesses

Lameness ranks among the primary welfare concerns in broiler production, prompting the creation of an innovative vision-based method for its timely identification (Aydin 2017). In the study, broilers assigned to one of five gait score categories were filmed via a digital camera while navigating a dedicated walkway. An image-processing pipeline extracted key kinematic parameters, including velocity, stepping cadence, stride distance, and lateral body sway (LBO). Correlation analyses yielded strong relationships between these metrics and gait scores: r = 0.831 (step frequency), 0.882 (step length), 0.844 (speed), and 0.861 (LBO). Additional statistical tests confirmed significant variations in these parameters across lameness levels, underscoring their reliability for distinguishing affected birds. Overall, the findings (Aydin 2017) validate the approach's effectiveness in lameness screening. Given the robust correlations and clear differentiations observed, this non-contact, automated framework shows promise as a continuous monitoring solution for commercial flocks. To enhance sensitivity for milder cases, future iterations could incorporate additional indicators—such as foot curling or wing positioning—or integrate with complementary behavioural analytics. Early lameness identification is critical, empowering producers and veterinary professionals to implement prompt interventions and mitigate suffering.

This study (Nakrosis et al. 2023) focuses on leveraging image processing algorithms to categorize poultry droppings into six distinct classes, representing varying levels of abnormality, thus enabling early detection of potential health issues. By utilizing deep learning approaches (Bist et al. 2023; Cakic et al. 2023), including different architectures, for segmentation and classification tasks, the proposed model achieved promising results. Specifically, the object detection rate reached an accuracy of 92.41%, with YOLOv5 demonstrating superior performance in classification, achieving an accuracy of 91.78% (Okinda et al. 2020). Moreover, the segmentation task yielded encouraging outcomes, with the K-means algorithm achieving a Dice coefficient accuracy of 0.88 (Mbelwa et al. 2023). Despite challenges related to unbalanced datasets, particularly in anomaly classes, future endeavors aimed at expanding the dataset hold promise for further improving accuracy and facilitating more nuanced analyses correlating with factors such as diet and poultry age (Aziz 2017; Wang et al. 2019; Zhu et al. 2021; Degu et al. 2023). Fig. 7 provides visual examples of four different distinct classes of droppings.

This research (Wang et al. 2019; Zhu et al. 2021; Nakrosis et al. 2023) underscores the potential of computer vision-based solutions in enhancing early disease detection and optimizing poultry health management practices.

Campylobacter (Hankel et al. 2022) represents a significant global concern as one of the primary bacterial foodborne pathogens, particularly within the poultry industry. The colonization of poultry flocks by *Campylobacter* poses a substantial risk, leading to contamination of food products. Effective and rapid detection methods for *Campylobacter* are crucial for implementing control measures to minimize contamination risks throughout the food supply chain, including logistical scheduling of slaughter operations. (Okinda et al. 2019; Igwaran et al. 2019; Ammar et al. 2021) This study (Hankel et al. 2022) assesses the efficacy of current and emerging detection technologies for *C. jejuni* in air samples under predefined prevalence conditions. Both non-invasive methods, utilizing volatile organic compound (VOC) analysis and quantitative polymerase chain reaction (qPCR), successfully detected the presence of *C. jejuni* and differentiated between varying levels of contamination in the study environment. However, electrostatic air samplers exhibited lower sensitivity in identifying *C. jejuni*-positive birds compared to cultivation-based techniques. Notably, VOC analysis demonstrated the potential to detect the presence of individual positive birds within the room, although further validation in field settings is warranted. These promising detection methods offer valuable tools for enhancing *C. jejuni* surveillance in poultry flocks, thereby mitigating the risk of human infection.

The two non-invasive air sampling approaches effectively identify *Campylobacter jejuni* contamination and quantify the proportion of infected birds within a flock (Hankel et al. 2022). As such, they represent valuable candidates for enhancing *Campylobacter* monitoring in broiler operations, although further rigorous evaluation and validation remain essential.

Biosecurity

Biosecurity in commercial poultry houses, particularly those housing broiler chickens, is paramount for maintaining flock health, preventing disease outbreaks, and ensuring optimal production efficiency. Broiler production facilities face numerous biosecurity challenges due to

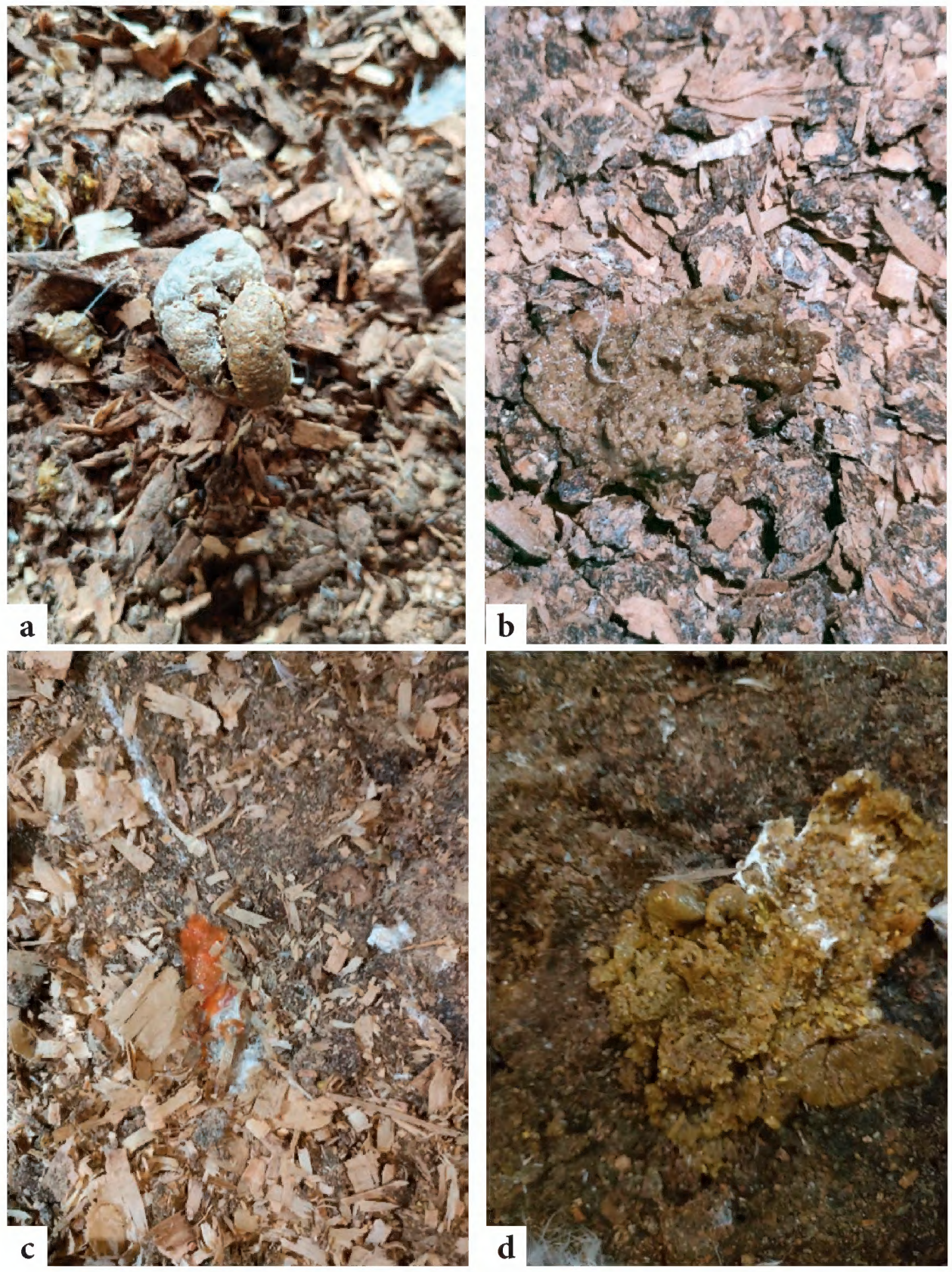

Figure 7. Examples of each of the four class images showing droppings on different types of litter. **a.** Normal; **b.** ABN1; **c.** ABN2; **d.** ABN3.

the intensive nature of the industry, with large numbers of birds housed in confined spaces. Effective biosecurity protocols aim to minimize the risk of pathogen introduction, spread, and transmission within and between flocks.

One of the primary biosecurity measures is controlling access to the poultry house (Tanquilut et al. 2020). Restricted access zones, including perimeter fencing, gates, and biosecurity checkpoints, help limit the entry of unauthorized personnel, vehicles, and equipment. Visitors and workers should follow strict biosecurity protocols, including changing into dedicated footwear and clothing, sanitizing hands, and adhering to designated entry and exit points. Additionally, maintaining strict hygiene practices is essential for minimizing disease transmission. Regular cleaning and disinfection of equipment, facilities, and vehicles help prevent the build-up and spread of pathogens. Cleaning and disinfection protocols should be tailored to target specific pathogens known to affect broiler chickens, such as Salmonella and *Campylobacter* (Benameur et al. 2023).

Another critical aspect of biosecurity in broiler production is managing the external environment to minimize the risk of disease introduction. This includes implementing rodent and pest control measures, securing feed and water sources to prevent contamination, and controlling wild bird access to the facility (Chen et al. 2021; Sammarco et al. 2023). Furthermore, biosecurity measures extend to the sourcing and management of day-old chicks. Hatcheries play a crucial role in disease prevention by implementing rigorous hygiene practices, sanitation protocols, and biosecurity measures to ensure the health of chicks before they are transported to broiler farms. Upon arrival, chicks should be housed in clean, disinfected facilities with proper ventilation and temperature control to minimize stress and susceptibility to disease. Regular health monitoring and surveillance are essential components of biosecurity in commercial broiler production. Early detection of disease symptoms, such as respiratory distress or lameness, allows for prompt intervention and treatment to prevent disease spread within the flock.

Overall, effective biosecurity practices are fundamental to maintaining the health, welfare, and productivity of broiler chickens in commercial poultry houses. By implementing comprehensive biosecurity protocols tailored to the specific needs and challenges of broiler production, producers can minimize the risk of disease outbreaks and optimize flock performance.

Conclusion

Artificial intelligence (AI) and machine learning (ML) are transforming poultry farming by enabling smart monitoring and automation, significantly enhancing productivity, sustainability, and animal welfare. For instance, AI-driven feed monitoring systems, such as sound-based algorithms, achieved 93% accuracy in detecting pecking sounds (Aydin et al. 2014) and a 0.994 correlation with feed intake at the group level (Aydin et al. 2015), while IoT-enabled dispensers reduced feed waste by 15% (Jebari et al. 2023). These technologies optimize resource use, as evidenced by automated feeding systems yielding a food conversion rate (FCR) of 4.4 and a growth rate of 8.88 g/day in young poultry (Peng et al. 2020). Ultrasonic water meters further enhance efficiency by detecting management issues like drinker leakage within 24 hours (Yao et al. 2021), supporting flock uniformity and performance. Health surveillance systems, including camera-based weighing with a 7.8% mean error (Mortensen et al. 2016) and lameness detection with correlations up to 0.882 (Aydin 2017), improve animal welfare by enabling early intervention. Additionally, UV-A light exposure reduced mortality rates by 75% (James et al. 2020), aligning with ethical standards. Economic analyses indicate that AI-driven systems, such as automated feeding and monitoring, can yield a return on investment within 2–3 years due to reduced feed and labour costs (Szőllősi et al. 2021).

Despite challenges, such as high implementation costs and scalability limitations in commercial settings with 30,000–50,000 birds (Peng et al. 2022), AI-driven systems provide real-time, data-driven solutions. Future research should focus on developing advanced algorithms and multimodal systems to further personalize farming practices, ensuring economically viable and humane poultry production through continuous innovation and training.

Author contributions

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